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## The effects of the dynamics of knowledge base complexity on Schumpeterian patterns of innovation: the upstream petroleum industry

### Journal Item

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## Abstract

This article analyses important changes in technological innovation in the upstream petroleum industry. It provides evidence that shifts in sectoral patterns of innovation over the petroleum industry's lifecycle from the 1970s up to 2005 were dependent on the dynamics of knowledge base complexity, a key dimension of an industry's technological regime. Accordingly, observed shifts in innovation patterns are understood to be the aggregated strategic response of industry innovators to changes in the technological regime. The article proposes a quantitative method for exploring knowledge base complexity and Schumpeterian patterns of innovation, and interactions between the two at the industry level. As the industry evolved, its knowledge base moved to higher orders of complexity creating a shift in the Schumpeterian pattern of innovation. Increased knowledge base complexity was found to alter Schumpeterian patterns from Mark I towards a 'modified' Mark II. Instead of coming predominantly from 'traditional' established oil operators, technological innovation was increasingly triggered by a new class of emergent integrated service companies – 'second tier' systems integrators of the upstream sector able to cope with increased knowledge base complexity.

**Keywords:** Schumpeterian innovation patterns, knowledge complexity, upstream petroleum industry

## 1 Introduction

This article addresses important changes in innovation patterns in the upstream petroleum industry from the 1970s to 2005, arguing that they can be explained by the dynamics of knowledge base complexity (KBC). A knowledge base is defined as complex if it involves integration and combination of different scientific and technological disciplines and requires a variety of competencies (such as R&D, design, engineering and production). We develop a quantitative method to explore KBC and show that its increase has shifted innovation patterns from a broadly Schumpeter Mark I to a 'modified' form of Schumpeter Mark II. The modification is that a higher concentration of technological innovation was not driven by 'traditional' established oil operators, working as 'first tier' systems integrators. Rather, it was led by a new class of emergent integrated service companies - 'second tier' systems integrators within the upstream segment of the industry able to cope with increasing KBC.

The petroleum industry has a relatively long and complex value chain, beginning with exploration and production of crude oil (upstream), to transport and refining (midstream), and ending with refining and retail (downstream). The upstream industry comprises a set of complementary activities: oil and gas exploration, together with heavy oil, condensates and tar sands; developing reserves for extraction, production over an extended lifetime; and finally decommissioning. It includes the business activities supporting and supplying these main activities. It is important to study KBC dynamics in the upstream segment because of changes that have occurred in both market environment and the nature of technological knowledge (Grant and Cibin, 1996; Helfat, 1997; Acha, 2002).

While the notion of technological regimes has proved useful in explaining inter-sectoral differences in sectoral patterns of innovation, the analysis of the relationship between technological regimes and patterns of innovation at different stages of development of a given industry remains rather unexplored (Krafft et al., 2014). Our research aims to show how the changing nature of sectoral patterns of innovation is intrinsically related to the dynamics of technological regimes. We provide a threefold contribution: firstly, we propose a dynamic reading of the concept of technological regimes and analyse structural transformation within the upstream petroleum sector over time. Secondly, we put the notion of KBC at the centre of our analytical framework. Thirdly, we propose a quantitative method using patent data to capture the dynamics of KBC and its relationship with Schumpeterian patterns of innovation. We empirically examine these ideas in the upstream petroleum industry, focusing on changes in technological opportunities and KBC.

Our study is unique in that it focuses on the dynamic relationship between KBC and the evolution of sectoral patterns of innovation. Most other works on technological regimes and sectoral patterns of innovation adopt a static cross-sectoral mode which ignores the important role of change in the nature of knowledge for industrial dynamics. Only the recent study by Krafft et al (2014) provides evidence regarding the relationship between change in knowledge base characteristics and industry structure in the pharmaceutical industry.

We also deal with temporal variation of innovation patterns at the sectoral level. Upstream petroleum comprises a multitude of players, some of whom are vertically integrated, and others who concentrate on particular sub-segments along the value chain. It also comprises different types of operators and a range of supply and service companies. Thus, as observed in other sectors by authors such as Corrocher et al (2007), at each point in time the industry and/or some of its segments may feature particular combinations of Schumpeterian patterns.

We focus our analysis on exploring shifts in overall patterns over time, and ask why they took place.

The article is organised as follows. Section 2 presents a dynamic reading of the concept of technological regimes and explores knowledge gaps in literature. In section 3 we introduce our method, showing how we measure technological opportunities, KBC, and dynamics of sectoral patterns of innovation. Section 4 presents our results, focusing on dynamics of technological opportunities, knowledge base complexities and Schumpeterian patterns of innovation. We then discuss the relationship between Schumpeterian patterns of innovation and the dynamics of KBC. Section 5 concludes.

## **2 Literature Survey**

We review three related bodies of relevant literature: Schumpeterian patterns of innovation; dynamics of technological regimes; and complexity.

### **2.1 Schumpeterian patterns**

In the Schumpeterian tradition, the distinction between Mark I and II has proved a useful analytical tool to distinguish varying sectoral patterns of innovation among different industrial sectors. In this article, we ask whether the Schumpeterian dichotomy is helpful in understanding how and why patterns of innovation differ in the same industry over time. Our intuition is that innovation patterns may gradually change as a result of technical change and the associated division of labour, creating a shift in the Schumpeterian pattern.

Schumpeter Mark I is characterized by creative destruction, where new firms play a major role in innovative activities and entry barriers are low. In contrast, creative accumulation is the main characteristic of Schumpeter Mark II, meaning that established firms play a major role in technological activities whilst it is challenging for new small innovators to enter (Schumpeter 1934, 1942). Authors such as Malerba and Orsenigo (1996) and Malerba (2007) found empirical support for the existence of these patterns.

Notwithstanding those key findings, these studies suffer from two limitations. First, the methodology employed does not allow for the observation of variations within a technological class or an industry, because the analysis relies on aggregated data. Second, it does not allow for the observation of temporal variation in sectoral patterns of innovation within industries, as the time dimension is removed. So, while it is widely accepted that patterns of innovation change over time, observations are based on average behaviour over time for specific technology fields or industries (Malerba and Orsenigo, 1996).

These limitations have been partly addressed in more recent studies. For example, Corrocher et al. (2007) observed the co-existence of both Schumpeterian patterns of innovation in the ICT industry. Grebel et al. (2007) provided similar evidence, highlighting the co-existence of large diversified and new technology firms within innovation networks in knowledge intensive industries like biotechnology and telecommunications.

Regarding the second limitation, Malerba and Orsenigo (1996) explicitly acknowledged the possibility of change in the nature of technological regimes over the course of time:

‘Some of these features of knowledge may change during the evolution of a specific sector or technology (degree of codification, independence, and complexity)’ (p. 97).

Malerba (2005) also argued that analysis of the knowledge base is key to developing an in-depth understanding of the innovative dynamics within sectors. Malerba (2006) added that ‘change in knowledge and knowledge base [...] goes to the heart of the evolution of the industries and of the factors affecting the change in industrial structure’ (p. 14-15). However, such change was conceived as very difficult to identify over significant periods of time even within single sectors, let alone the identification of regularities across a range of industrial sectors.

## **2.2 Technological regimes in a dynamic perspective**

The concept of technological regimes was introduced by Nelson and Winter (1982), referring to the knowledge environment in which firms operate, or in which their problem-solving activities take place. More recently, four building blocks were identified: technological opportunity, the appropriability of innovations, their cumulativeness, and knowledge base properties (Breschi and Malerba, 2000). Technological opportunities refer to the likelihood of innovation in a particular sector resulting from a given investment in search processes. Over the industry life cycle (ILC), technological opportunities may significantly change, suggesting their dynamic nature. The standard ILC model assumes that opportunity conditions decrease as industries mature (Klepper, 1996). However, statistical analysis (McGahan and Silverman, 2001), case studies of mature industries, and research on innovation in low-tech industries (Robertson et al., 2009; Hirsch-Kreinsen, et al., 2006; Von Tunzelmann and Acha; 2005) show that this is not necessarily the case.

The properties of the knowledge base which shape innovative activities constitute a synthetic framework encompassing the degree of specificity, tacitness, complexity and independence. Specificity refers to the scope of applications within a particular knowledge domain.

Tacitness refers to the extent to which knowledge is not articulated in standard formats such as blue prints. Degree of independence refers to the extent to which knowledge that is relevant to innovative activities can be separated. Like other dimensions of technological regimes, these properties of the knowledge base can change over time as a result of new application, inter-industry knowledge flow, codification practices (Steinmueller, 2000), and new instrumentation or computational capabilities (Arora and Gambardella, 1994).

Changes in one or more of these dimensions of technological regime are likely to have important implications for sectoral patterns of innovation (Malerba and Orsenigo, 1996; Malerba, 2007). We test this theory in upstream petroleum with particular emphasis on the dynamics of KBC. According to literature on technological regimes (Malerba and Orsenigo, 1997; Breschi and Malerba, 2000), a knowledge base is defined as complex if (a) it involves integration and combination of different scientific and technological disciplines and (b) requires a variety of competencies (such as R&D, design and engineering, and production) for innovative activities. So far, the role of KBC has been addressed only by a few studies, including Vale and Caldeira (2008) investigation of the footwear industry and Iizuka (2009) account of structural change in the Chilean salmon farming industry.

### **2.3 Complexity**

Complexity has been defined in several ways. A key concern of scholars writing on complexity (Wang and von Tunzelmann, 2000) is the volume of interdependencies and degree of interaction between the elements of a system. This specific notion of knowledge complexity matters when:

‘the opportunities to generate new knowledge are conditional on the identification and integration of the diverse bits of complementary knowledge that are inputs into the knowledge production process’ (Antonelli, 2003, p.507).

This kind of complexity shapes industrial dynamics, since the recombination of both pre-existing and new information is key to generating new knowledge and introducing systemic innovations (Chesbrough and Teece, 1996).

Knowledge indivisibility is the outcome of a process whereby systemic knowledge serves new functions which are not achievable by individual bits of knowledge. In sectors with high levels of such complexity, successful innovation is not possible without a full understanding of the compatibilities of diverse technologies. Because the source of this complexity is often systemic innovation (Chesbrough and Teece, 1996), it is labelled systemic complexity.

### 3 Method

We combine three related methods: patent analysis to measure the dynamics of technological opportunities; measurements of KBC; and measurements of sectoral patterns of innovation.

We analyse the transformation of sectoral innovation systems in upstream petroleum using the Derwent Innovating Index - the patent database which classifies all upstream petroleum industry patents in class H01. This class covers exploration, drilling, well services and stimulations, production and their sub segments of the upstream petroleum industry. We rely on the records of Derwent International Patent Families (IPFs), which group similar inventions registered in different territories, in order to avoid multiple counting of the same invention registered in different countries. Patent counts are used as a proxy to capture the dynamics of innovative performance.

Patent data is the only rigorously classified information on technological innovation covering both long time periods and a wide range of countries. The advantages and limitations of patent data for the analysis of innovative activities is a widely discussed issue within literature. It is particularly important to consider its limitations, such as systematic biases in data which may produce distorted results if not treated properly. The main disadvantages include (Pavitt, 1985; Griliches, 1990): (i) Not all inventions are legally patentable everywhere. The classic example is software which in many countries is protected by copyright. Moreover, the patenting scope may differ from one country to another depending on their particular patent law; (ii) Due to differing institutional structures in various countries which affect the length, time and level of protection, an inventor's incentive to file for patents vis-à-vis use other forms of protection varies substantially; and (iii) Propensity to patent varies across industries. Propensity to patent can also vary over time because of changing knowledge dynamics (such as growth of software based technologies) , the changing dynamics of the sector towards service companies which are more reliant on their tools and techniques, and changing competitive pressures in the sector.

While patents are only imperfect measures of innovation, our results are less affected because the conclusions in this study are based on the analysis of trends rather than absolute levels of the variables. Therefore, we do not expect imperfections to significantly impact trend analysis.

#### 3.1 Measurement of technological opportunities

Following previous studies, such as Andersen (2005) and Fai (2007), we use patenting growth rate to capture the dynamics of technological opportunities in upstream petroleum. We employ variation in patenting rate to examine how technological opportunities change over time.

### **3.2 Measurement of Knowledge base Complexity**

We aim to understand how the level of KBC evolved over the ILC in different periods and how major innovators coped with its dynamics.

According to the definition introduced in section 2.3, proxies to measure complexity should consider the links and interactions between different elements of the knowledge base and capture the recombinant nature of knowledge. In order to measure systemic complexity, network representation of the knowledge base is very relevant. According to this view (Saviotti, 2011; Krafft and Quatraro, 2011), the knowledge base has a co-relational structure comprised of nodes and links between these nodes. Nodes are technology classes and links represent relationships between technologies connecting nodes together. The measure of systemic complexity should consider the structure of relationships between different knowledge domains. The dynamics of complexity are understood from changes in the pattern, strength of linkages and interactions between the nodes.

Network analysis indicators treat knowledge as an integrated system in which both the building blocks of the system (nodes) and their interactions (ties) are investigated at the same time. This enables us to monitor how the knowledge structure changes over time when new technologies emerge, diffuse and are integrated into the system or the old ones expire, are abandoned or disconnected from the knowledge base (Krafft and Quatraro, 2011).

Proxies to measure complexity consider the network of links and interactions between different elements of the knowledge base and capture the recombinant nature of knowledge and its endogenous complexity. The knowledge base has a co-relational structure comprising nodes and links between these nodes (Saviotti 2009; 2011). Nodes are seen as technology classes, and links represent relationships between technologies connecting nodes together. The dynamics of complexity are understood by changes in the pattern and strength of linkages and interactions between the nodes. Social Network Analysis (SNA) is employed to examine the dynamics of systemic KBC in upstream petroleum. Following Krafft et al (2011), *weighted average degree* of network *centrality* (WADC) was used to measure the systemic complexity of the industry's knowledge base (see Appendix 1).



When the speed of formation of new nodes outweighs the formation of links, the network becomes less connected and systemic complexity (WADC) decreases. In contrast, when the formation of new links is swifter than the appearance of new nodes in the knowledge network, network connectivity increases (Saviotti, 2011), signalling the rise of systemic complexity (WADC).

### **3.3 Measurement of sectoral patterns of innovation**

The indicators selected for the analysis of the dynamics of sectoral patterns of innovation are based on previous studies (Malerba and Orsenigo, 1996; Breschi and Malerba 2000). They are: concentration of innovative activities (C); the number of innovative firms (F); share of new entries (NE) to the innovation system in terms of the proportion of patents registered by new innovators.

Although the variables of this inter-temporal research are similar to previous cross-sectoral studies, their operational correspondence with archetypical Schumpeterian patterns of innovation is interpreted differently. Due to the dynamic nature of the analysis, we are more interested in the variables' trends than in their values in cross-sectional designs. In other words, our interpretation is based on relative change of variables over time, indicating whether at different points in time upstream petroleum was moving closer to a typical Mark I or Mark II type.

## **4 Results**

Our results are compiled in five sub-sections: our periodization of trends of technological opportunities; the dynamics of KBC over those periods; the consequences of that complexity; the dynamics of Sectoral patterns of innovation; and the resulting changes in Schumpeterian patterns of innovation.

### **4.1 The trend of technological opportunities**

In figure 1 we present the innovation trend in upstream petroleum according to the number of patent applications in the US Patent Office (solid line) which reflects the trend of technological opportunities. The dash-line shows the trend of total patenting in USPTO at 1% scale to control for changes in the overall level of patenting. That is, to examine whether observed dynamics of innovation is a reflection of technology push from other sectors, or the result of internal dynamics within the upstream petroleum industry.

From figure 1, we can identify three distinct periods of technological innovation over the last four decades. From the early 1970s until mid-1980s, we observe a growing trend where the

number of US patent applications almost doubled (p1). The second period runs from 1984 to 1994, with a negative trend in innovation (p2). The third period begins after 1994 where we see a surge in innovation (p3).

**INSERT here Figure 1: the number of US patent applications over time**

The first period, (early 1970s to mid-1980s,) was characterised by a growth and diversification strategy driven by investment in advanced technology to expand supply sources in more challenging reservoirs. The gap between supply and demand was widening. Major oil operators lost their monopoly on global reserves leading to the first and second oil shocks (Grant and Cibir, 1996). The rise in patents can be explained by upstream factors, including high oil prices. Such technological efforts were enormously successful, bringing down exploration and production (E&P) costs and increasing reserve replacement ratios (Fagan, 1997). The stable trend of total patenting (dash line) in this period confirms that the rise of innovation is not an overall global innovation trend but was driven by upstream industry-specific factors.

The second period (mid-1980s to the mid-1990s), was characterised by oil price cuts and excessive supply combined with stiff competition. Excessive supply was partly due to new technologies able to access offshore fields (e.g. in North Sea and West Africa) which triggered strategic change in terms of greater static and dynamic efficiency among operators. Cost cutting, specialization and change of strategic focus emerged as established trends (Grant and Cibir, 1996) so that technological innovation was no longer a top priority. The main focus was on increasing flexibility and responsiveness to change (Weston and Johnson, 1999). Major oil operators restructured whilst new smaller specialised supply and service companies followed horizontal as well as vertical integration strategies (Babusiaux et al., 2004; Barreau, 2002). Excessive supply and low oil prices acted as a disincentive for innovation. Thus, compared to a 15% decline of patents in upstream petroleum, over the period we observe an increase in total patent awards of more than 70% (figure 1).

The third period has more complex dynamics. The sharp upward trend in innovation from 1994 was driven neither by higher oil prices (they did not increase for a further six years) nor by external technology (see the dash line in figure 1). On the contrary, difficult access to oil fields particularly in OPEC countries pushed operators to seek alternative sources. As suggested by the rise of exploration and development costs (U.S. EIA, 2011) and low reserve replacement ratios (Bagheri and Di Minin 2015), this situation created an unprecedented

demand for technological innovation, especially concerning exploration and production in places such as ultra-deep waters in the Gulf of Mexico. Technological advances are also reflected in the rise of well completions (WRTG, 2008)

Harnessing new technological opportunities, however, was not a priority for international operators who continued their quest for efficiency under prolonged low oil price conditions. In response to low price and volatile environmental pressures, they cut R&D investments, conducted mega mergers and acquisitions for scale efficiencies, and outsourced a wider range of activities to service companies.

Meanwhile, service companies increased their R&D investments (Bagheri and Di Minin 2015) to meet new market conditions, as also reflected in their increasing share of patents compared with declining share of operators (Maleki, 2013). Growing supply and service companies (such as Schlumberger, Halliburton, Baker Hughes, and Weatherford) gradually began to provide a broad range of packaged services to meet their client's expanding needs for more ambitious exploration and development projects (Barreau, 2002). As their 'integrated solutions' gained momentum, supply and service companies cultivated project management and integration capabilities, previously the territory of major oil operators.

These trends nudged service operators towards unprecedented consolidation (Barreau, 2002), an organizational industry-wide response to new technological imperatives (Teece and Armour 1976) that spurred a wave of innovative solutions. Overall, the intensity of E&P activities and their knowledge content significantly increased over time, which led Rajan (2011) to observe that 'if all technological innovations produced by the oil and gas industry were added up, they would probably rival NASA's space program or the Industrial Revolution.'(p. 11).

#### **4.2 The dynamics of knowledge base complexity**

The dynamics of KBC in the upstream petroleum industry are presented in figure 2 using the *WADC* measure. Systemic complexity shows a downward trend over most of the first period (p1), which indicates decreasing connectivity within the knowledge network. This process is driven by a higher rate of creation of new nodes (or new technological classes), compared to new links between new and existing nodes (Saviotti, 2011). In this phase, the sector is mostly in its random search period and exploration strategy is dominant. Because the structure of the knowledge base is changing and is not yet established, both cognitive barriers to entry and the degree of knowledge cumulativeness are relatively low.

**Insert here Figure 2: Dynamics of knowledge base complexity in the upstream petroleum industry**

Historically, this was the period of rapid technological progress, when technologies like 3-D seismic and horizontal drilling were first introduced. When promising new technological fields are explored, it takes time for innovators to understand the relationships between new and existing knowledge domains. The introduction of new technologies may be expected to create new but poorly connected nodes, and temporarily reduce the systemic connectivity of the knowledge network (Saviotti, 2011). The first period in upstream petroleum reflects this hypothesis.

The situation began to change when the direction of systemic complexity reversed in the beginning of the second period (p2) around 1986, as connectivity within the knowledge network increased. This trend continued almost up to the end of p3. The diffusion and establishment of new technological fields explored in p1 helps to explain the changing overall pattern in p3, when the rate of creation of new links overtakes the rate of emergence of new nodes. It does not imply that the emergence of new technological domains stopped, rather that it became lower compared to the established technological fields.

By the end of p1 and during early p2, the most promising fields had become known to the industry's incumbents. Historically, this is when integrated service companies began to emerge. As it was difficult for established operators to manage the increasing range of specialized sub-contractors in different technical domains and coordinate technological interfaces, integrated service companies took on this role. They introduced total and integrated solutions combining related technologies in unified packages (Barreau, 2002; Chafcouloff et al., 1995). Following Krafft and Quatraro (2011) and Krafft et al. (2014), we argue that search strategies of industry players gradually became organized rather than being random. Explorative behaviour was gradually replaced by exploitative strategies applied in the most productive technological areas. Innovation increasingly happened within technological classes which proved promising and fruitful, with a lower dispersion of R&D investment across fields. As a result of emergent complementarities, the knowledge base of the sector is not easily divisible or decomposable. The rise of knowledge network connectivity over most of p2 reflects these dynamics.

The post 2002 decline in WADC seems odd, but still compatible with our theoretical argument. It resembles a period of technological discontinuity whereby the speed of new links in knowledge networks falls behind new nodes, so knowledge connectivity declines. We

suggest such change a trend is a consequence of the fact that information about knowledge links is delayed (in the data set) compared to information about the nodes. In other words, systemic innovations which result from combinations (links) of previous innovations (nodes) appear later.

#### **4.3 The Expected Consequences of Knowledge Base Complexity**

During the early phases (p1 and early p2) of the ILC, the complementarities between new and old knowledge domains were not fully explored and knowledge linkages were not fully operational. Access to a wide range of complementary knowledge was not necessary for the innovation process. Therefore, we expect to observe new entrants taking a greater role relative to big and established companies when the sector moves towards a Schumpeter Mark I pattern.

When systemic complexity increased in periods 2 and 3, the sector moved towards a more organized search period and exploitative strategies became more pervasive (Krafft et al., 2011). Core technological domains were defined, technological trajectories were relatively clear and most productive complementarities and technical interdependencies were explored by industry participants. Innovative companies which connect and integrate different bits of knowledge were able to benefit from economies of scale and scope in both knowledge generation and exploitation processes.

High systemic complexity presents strategic advantages for technologically diversified actors who occupy key positions within knowledge networks, compared to marginal players (Antonelli, 2003). As a result, more knowledgeable incumbents are expected to be better placed to benefit from cross-fertilization between different knowledge domains and their wide range of applications. The entry barriers for new companies tend to be higher and growth opportunities for small ones limited, pushing the sector towards a Schumpeter Mark II pattern. These propositions are examined next.

#### **4.4 Dynamics of Sectoral patterns of innovation in upstream petroleum**

In this section, we analyse the direction of change in the sectoral pattern of innovation of upstream petroleum industry. As shown by Corrocher et al (2007), the same industry can comprise a combination of two Schumpeterian patterns of innovation. In the very early days, upstream petroleum resembled a Schumpeter Mark I dominated by individual entrepreneurs until a monopolistic structure similar to Mark II materialised because of the emergence of Standard Oil. Although the dismantling of Standard Oil in 1911 decreased the level of

concentration, the fundamental oligopolistic structure dominated by the ‘Seven Sisters’ remained until the 1960s when increased competition shifted the industry in the direction of Mark I again (Inkpen and Moffett, 2011).

In this article, a more detailed account of the dynamics of the sector is provided for the period 1970-2005. Following the extant literature (Malerba and Orsenigo, 1996), we use a set of variables to examine how the sector evolved over the three periods (see section 3.3).

**INSERT here Table 1: Expected Schumpeterian Patterns of Innovation in a dynamic perspective.**

Table 1 summarizes the archetypical Schumpeterian patterns of innovation and the direction of the variables over time that we expect to observe in each typical mode (see 3.2.2). A Schumpeter Mark I sector is relatively open to the entrance of new or small firms. Therefore, we expect that new firm entry and the number of innovating firms will increase over time, resulting in a decrease of the concentration of innovative activities. Malerba and Orsenigo (1997) term this process ‘widening’.

In contrast, a typical Schumpeter Mark II sector is relatively closed to new or small innovators and works in favour of large innovators. Therefore, we expect to observe a decreasing trend in the contribution of new firms. The number of firms may be relatively stable (as shown in table 1) or even decrease over time, depending on the size of existing firms. This implies a rise in concentration of innovative activities which Malerba and Orsenigo (1997) term ‘deepening’.

Comparing the observed trends with the evolution of technological opportunities (see table 1) helps to reveal the dominant pattern. We stick to the three main periods defined in section 3. In order to smooth the trends and ignore short term fluctuations, we collapse the data, as shown in figure 3. The length of the first period is 14 years, but the length of both the second and third periods is 10 years. Therefore, we divide p1 into one introductory sub-period (p1-0) and two other sub- periods (p1-1, p1-2). This means that all three main periods cover 10 years with two 4-year sub periods at both sides and a two year gap in the middle, leaving out the introductory sub-period of p1-0. Using this periodization helps to control for the impact of change in technological opportunities on the selected variables, and therefore helps to unravel the role of KBC in the dynamics of sectoral patterns of

**INSERT here Figure 3: Periodisation of the Analysis**

**4.4.1 Concentration and number of innovators**

The top part of figure 4 shows the trend of concentration over time for different size groups using a corrected version of Herfindahl index of concentration. This measure is used to explore how the relative share of big vs. small innovators in the sector changes over time. The advantage of this corrected version is that it controls for small sample bias (Corrocher et al., 2007). We repeated the indicator for different subsets of companies defined by innovation size (for  $N < 40$ ,  $N < 100$ ,  $N > 40$ ,  $N > 100$  and all companies:  $N$  is the number of patents each company holds) to check the robustness of the results in different size groups. The top left side of the figure 4(a) displays concentration ( $C$ ) for large innovation size group and top right side of the figure 4(b) shows it for smaller sizes. Regardless of the size categories, all of the indicators present an overall U shape pattern reaching their lowest points in p1-2 or p2-1. The two lowest figures show the number of innovative firms over time, by innovation size.

**INSERT here Figure 4: Concentration of innovative activities (a & b) and number of innovative firms (c & d): by innovation size**

According to these figures, concentration ( $C$ ) decreases in p1 (and even up to p2-1 for larger groups). In parallel, firm numbers ( $F$ ) increase in almost all size categories. High technological opportunities driven by high oil prices seem to have worked as a powerful incentive for smaller firms to catch up with major innovators. The increasing number of innovative companies in all groups also confirms the key role of new innovators in p1.

When oil prices collapsed in p2-1, innovative efforts were no longer rewarding within the industry. Over p2,  $F$  slightly decreased and  $C$  took a clear upward trend. One reasonable explanation is the higher vulnerability of some smaller firms, when continued low opportunity dries up innovative efforts. Due to the high risk and uncertainty involved in innovative activities, firms cut R&D investments in low profit conditions, though with delays (Acha, 2002; Wintersteller, 1993). As discussed in section 4.1, the trend of patents is negative in p2. Increasing concentration of innovative activities, combined with reduction in the number of innovative firms, suggests vulnerability of smaller firms leaving the system of innovation. Indeed, p2 is the only period with negative net entry.

The beginning of the third period (p3) presents an interesting and puzzling pattern. By the end of p2 and the beginning of p3, a new wave of innovative entry can be noted, resulting in a sharp rise of  $F$  (fig 4d) in all size categories, excepting super big innovators ( $N > 100$ ) (fig

4c). This was driven by the jump in technological opportunities observed after p2-1. Although F transforms from a negative trend in p2 to a sharp positive trend in p3, there is no expected corresponding drop in C. In contrast, C continues its upward trend which is reinforced over p3.

This pattern reflects the relative low and weakening share of new entrants in p3, compared to big incumbents (figs 4a & b). In addition, the short term jump of F before p3-1 (fig 4b) turned into a relatively stable trend in p3, whilst concentration gained momentum.

These patterns suggest a fundamental difference between p1 and p3. On the one hand, flourishing opportunity environments in both periods encourage new innovators to enter the sector - reflected in the rise of F. On the other hand, C presents an opposite trend - decreasing in p1, but increasing in p3. These different behaviours were driven by the changing nature of technological regimes, especially the rise of KBC. In particular, we observe that the increasing systemic complexity in p3 was associated with a higher concentration of innovative activities.

To summarise, our results show that during p1, small innovators benefited from abundant opportunities because of low systemic complexity, which was no longer the case in p3. Systemic complexity in p3 increased the cognitive barriers to entry for small and newcomer companies. Although high technological opportunities emerged and were driven by knowledge recombination processes (see section 4.2), they were mostly exploited by knowledgeable and technologically diversified companies, with integrative and combinational capabilities. Small and new firms continued to innovate in specialized niche technical areas, but became less relevant.

**4.4.2 Share of new entry to the system of innovation**

This section analyses the ability of new innovators to contribute to the development of the knowledge base of the industry in comparison to that of incumbents. Table 2 shows the number of patents (by international patent family IPF) of existing and new firms in each sub-period; and also the new innovators' share of patents (NE) in each sub-period. This is measured for three different innovation sizes of firms (with minimum patent size of 1, 5 and 10), in order to gain insight into the role of size for successful entry.

**INSERT here Table 2: New entries to the innovation system by different innovation size**



According to table 2, the 1% increase in the share of new entry during period 1 (p1) reflects the rise of success rate of new innovators. Growth of new entries seems higher for bigger innovators (about 2% and 4% for 5 and 10 IPFs minimum size), suggesting the increasing possibility of advancement among larger firms. Overall, the new entry indicators confirm increasing opportunities over p1 for new innovators of all sizes.

The transition from p1 to p2 is accompanied by a 10% reduction of new entrants for all size ranges. The arrival of low opportunity conditions in p2 works against new entry, as expected returns on R&D are reduced. Over p2, when low opportunity conditions established themselves and companies adjusted to the external shock, some new entrants' losses were recovered. This is reflected in the rise of new entrants' share of innovators. Such a result is rather counter intuitive, because low opportunity conditions are not normally conducive to new entries.

One reasonable explanation, supported by data from Weston and Johnson (1999), is that new innovative companies emerged as a consequence of accelerated outsourcing by operators whereby part of the innovation process was transferred to a new class of agents (service companies). Consequently, we attribute the rise of new entries over p2 to the emergence of a new division of innovative labour in the industry.

The distinction between short-term and long-term responses to low opportunity conditions within the sector is an interesting finding. The short-term response of industry to low opportunities was to reduce new entries. However, the long-term response entailed the formation of a new division of innovative labour, or more precisely a new 'industry architecture' (Brusoni et al., 2009). This favoured new entrants and triggered new knowledge dynamics. Transition from the low opportunity conditions of p2 to high opportunity conditions in p3 amplified the number of entries, as reflected in the continued rise of NE for all size ranges from p2 to p3.

Over p3, we observe a relative reduction of new entrants in all groups, to their lowest levels over the whole 1970-2005 period. In contrast to the high opportunity conditions of p1 over which new entries experienced their maximum level, the possibility of new entries over p3 is most limited. *Ceteris paribus*, the standard theory of patterns of innovation predicts a positive relationship between opportunities and new entries. These predictions however are conditional on the nature of technological regimes. For example, high new entry is expected under low cumulativeness conditions when potential innovators are not at major disadvantage

with respect to incumbent firms (Breschi and Malerba 2000). Our analysis in sections 4.2 and 4.3 suggests that the difference between p1 and p3 in terms of new entries can to a significant extent be attributed to the dynamics of KBC. New entrants are at a high disadvantage in p3 compared to p1 because of the change in underlying technological regimes. The rise of systemic complexity over p3 involves higher cumulativeness, implying higher cognitive barriers to entry, which hindered the exploitation of existing technological opportunities by new and small companies in this period.

**4.5 Schumpeterian patterns of innovation and KBC**

So far, the dynamics of the sectoral pattern of innovation in the upstream petroleum industry have been analysed using three indicators over the main periods. Table 3 summarizes the changing pattern of these indicators over each period. The arrows in table 3 specify the magnitude of changes in the indicators over that period. Accordingly, p1 is characterised as strong Mark I, because of a considerable reduction in the degree of concentration (C), a large increase in the number of firms (F) and the rise of new entrants (NE).

**INSERT here Table 3: Observed Schumpeterian patterns of innovation**

The second period presents a pattern which is similar to Mark II, although its intensity seems weak. C began a slight upward trend and F reduced to some extent, as technological opportunities were relatively low. Although NE shows an upward trend over p2, this can be explained by the increased reliance of oil operators on outsourced services, a trend driven by low oil prices (Weston and Johnson, 1999). In the absence of this structural change, higher concentration and a lower number of innovative firms and new entries would probably have been observed. Hence, this period could be labelled as Mark II, but with some effect of structural change on new entries. These results suggest that KBC contributes to explain change in innovation pattern as the industry entered p2, because increased connectivity within the knowledge network meant larger incumbents were in a better position to exploit technological independencies.

The signs of Schumpeter Mark II are considerably stronger when technological opportunities increase over p3 (as the patterns of indicators show in table 3). Although technological opportunities are high, new entries are reduced and the number of firms stays relatively stable. Most importantly, the upward trend of concentration accelerates. When the three indicators are combined, comparing table 1 and table 3 shows the emergence of a progressively stronger Mark II, in which the relative advantage of big innovators coincides

with higher KBC. The rise of technological complexity in the sector was driven by more sophisticated upstream exploration and complex production projects. As a result, only big technologically advanced companies had access to the required range of sophisticated technologies required for complex projects.

Our results also suggest that change in technological opportunities tends to affect the pace of change in existing patterns of innovation. The existing pattern of innovation is weakened when changing from high to low opportunity (as observed over the transition from p1 to p2) and is reinforced when changing from low to high (as observed over the transition from p2 to p3). However, this evidence by itself is unable to explain the shift from Mark I to Mark II. This is best understood by looking at the two extremes of p1 and p3, when two different patterns of innovation are observable with high technological opportunities. If the concept of technological regimes is convincingly to explain the shifts in the mode of Schumpeterian pattern, other factors should be taken into account. In the case of upstream petroleum, we stress the role played by systemic KBC. Reduction of systemic complexity over p1 is consistent with Schumpeter Mark I. When systemic complexity of the knowledge base increases in early p2, the features of Mark II emerge in the sector. Then, higher opportunities in p3 reinforce this pattern.

These findings fit well with the propositions outlined in section 4.3. As predicted, the upstream sector seems to move toward Mark I over p1 and shift towards Mark II over p3. This leads us to posit a novel analytical framework which explains how the upstream petroleum industry evolved through different patterns of innovation in parallel with technological opportunities and KBC. The impact of the combination of these two dimensions of technological regimes on change of pace and mode of Schumpeterian pattern of innovation over the three periods is demonstrated in a 2x2 matrix in figure 5. The vertical axis specifies high vs. low technological opportunities and the horizontal axis represents the pace of systemic complexity. As argued in section 3, the dynamics of systemic complexity could favour the dominance of two different modes of Schumpeterian pattern of innovation (Mark I on the left and Mark II on the right of the matrix differentiate these two types). Increasing (decreasing) technological opportunities tends to reinforce (weaken) the pace of existing pattern, whether it is Mark I or II, but do not alter its mode.

**INSERT here Figure 5: Technological regimes and innovation patterns**

## **5 Conclusions**

This article argues that shifts in sectoral patterns of innovation are intrinsically related to the dynamics of technological regimes. We provide a threefold contribution. Firstly, we propose a dynamic reading of the concept of technological regimes to understand structural transformations of an industry over time. Secondly, we conceptualize, placing KBC at the centre of our analytical framework. Thirdly, we propose a quantitative method using patent data in order to capture the dynamics of KBC and their relationship with sectoral patterns of innovation.

Our study highlights three distinct periods starting from 1970. The first period corresponds to high oil prices when operators dominate and actively invest in technology. The second period is characterised by a collapse in oil prices and a reduction in R&D investments, with a negative effect on innovation and an expansion of specialised supply and service companies. The third period saw the gradual emergence of new large integrated service companies which increased R&D investments and offered innovative solutions to complex upstream projects.

We focus on the co-evolution among KBC, technological opportunities and sectoral patterns of innovation. Our evidence suggests that decreasing systemic complexity tends to be associated with a transition towards Schumpeter Mark I, while the rise of systemic complexity implies a shift towards Mark II. Nonetheless, it is also evident from our findings that the Schumpeterian dichotomy is not completely adequate to capture the dynamics of complex sectoral innovation systems. We observed that the third and last period of the study in upstream petroleum is not a typical Mark II, but rather a modified type in which a new class of innovators emerges to cope with increasing technological complexity. These innovators were integrated service companies playing the role of ‘integrators of technological knowledge’ (Maleki, 2013; p. 98).

Other empirical analyses show that specialisation strategies of operators and service companies can entail varying innovation trajectories due to their different ‘technology frames’ (Acha, 2002). The pattern of division of labour in p3 allowed service companies to take an important position as technological innovators. Following the model proposed by Jacobides (2006), oil operators remained ‘first tier’ system integrators as they provided a ‘new product architecture’ and/or new ‘field development models’ (Acha, 2002, p. 82). However, as systemic complexity increased, a significant proportion of innovative activities were undertaken by service companies, acting as ‘second tier’ system integrators. As observed in other complex domains such as the aircraft industry, co-existence of multiple systems integrators along the same value chain is possible.

We also argue that the dynamics of technological opportunities alone cannot explain the observed shift of mode in innovation pattern, although they can help to reveal changes in the pace or strength of existing Schumpeterian patterns. In the period under consideration, while the nature of knowledge components underlying the sector may have not changed considerably, the intensity of interactions between knowledge components was progressively increasing, leading to higher systemic complexity and knowledge cumulativeness of the sector. Only when the dynamics of technological opportunities are analysed in combination with those of KBC, can they convincingly explain the dynamics of Schumpeterian patterns both in terms of pace and mode. Change in systemic complexity could alter the Schumpeterian mode, while a rise (or decline) of technological opportunities tends to weaken (or strengthen) the existing mode without altering it. This situation characterises a (modified) Schumpeter Mark II mode.

This article offers novel insights into our understanding of Schumpeterian patterns of innovation, while also providing a wider contribution to a strand of literature in which business history interacts with economics and management. In this sense, the dynamics of technological complexity constitute an important, albeit less understood, factor behind firm-level strategy and the evolution of an industry structure (see Mowery, 2015).

Our analysis offers promising opportunities for further research. In particular, since it is confined to upstream petroleum, it would be interesting to examine the transferability of our findings to other industrial sectors.

## References:

- Acha, V. L., 2002. Framing the past and future. SPRU. Brighton, Sussex. PhD dissertation.
- Andersen, B., 2005. Paradigms and Trajectories of Technological Opportunities 1890-1990. Handbook of Quantitative Science and Technological Research, H. Moed, W. Glanzel and U. Schmoch, Springer, NL, 133-161.
- Antonelli, C., 2003. Knowledge Complementarity and Fungeability: Implications for Regional Strategy. *Regional Studies*, **37**(6-7), 595-606.
- Arora, A. and A. Gambardella, 1994. The changing technology of technological change: general and abstract knowledge and the division of innovative labour. *Research Policy* **23**(5), 523-532.
- Babusiaux, D., J Favenne et al, 2004. Oil and Gas Exploration and Production: resources, costs, contracts. Paris: Editions Technip.
- Bagheri, S.K. and Di Minin, A., 2015. The changing competitive landscape of the global upstream petroleum industry. *The Journal of World Energy Law & Business*, **8**(1), 1-19.
- Barreau, S., 2002. Innovations and External Growth Strategy: the Case of Oil and Gas Supply and Service Companies. *Oil & Gas Science and Technology - Rev. IFP* **57**(2), 193-203.
- Breschi, S. and F. Malerba, 2000. Sectoral innovation systems: technological regimes, Schumpeterian dynamics, and spatial boundaries. In Edquist C. and McKelvey M. D (Eds.), *Systems of innovation: growth, competitiveness and employment*. Cheltenham, Edward Elgar, 249-261.
- Brusoni, S., M. Jacobides and A. Prencipe, 2009. Strategic dynamics in industry architectures and the challenges of knowledge integration. *European Management Review*, **6**(4), 209-216.
- Chafcouloff, S., G. Michel, et al. 1995. "Integrated services." from [http://www.slb.com/~media/Files/resources/oilfield\\_review/ors95/sum95/06951125.ashx](http://www.slb.com/~media/Files/resources/oilfield_review/ors95/sum95/06951125.ashx).
- Chesbrough, H. W. and D. J. Teece, 1996. Organizing for Innovation (Cover story). *Harvard Business Review*, **74**(1), 65-73.
- Corrocher, N., F. Malerba, and Montobbio F, 2007. Schumpeterian patterns of innovative activity in the ICT field. *Research Policy*, **36**(3), 418-432.
- Fai, F., 2007. A structural decomposition analysis of technological opportunity, corporate survival, and leadership, *Industrial and Corporate Change*, **16**(6), 1069-1103.
- Fagan, M. N., 1997. Resource Depletion and Technical Change: Effects on U.S. Crude Oil finding Costs from 1977 to 1994. *The Energy Journal*, **18**(4), 91-106.
- Grant, R.M. and Cibin, R., 1996. Strategy, structure and market turbulence: the international oil majors, 1970–1991. *Scandinavian Journal of Management*, **12**(2), pp.165-188.

- Grebel, T., J. Krafft, and Pier-Paolo Saviotti, 2007. On the life cycle of knowledge intensive sectors. *Revue de l'OFCE*, 63–86.
- Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4), 1661-1707.
- Helfat, C.E., 1997. Know-how and asset complementarity and dynamic capability accumulation: The case of R&D. *Strategic Management Journal*, 18(5), pp.339-360.
- Hirsch-Kreinsen, H., D. Jacobson, and Robertson PL, 2006. Low-tech' industries: innovativeness and development perspectives - a summary of a European research project. *Prometheus*, 24(1), 3-21.
- Iizuka, M., 2009. Standards as a platform for innovation and learning in the global economy: A case study of the Chilean salmon farming industry. *International Journal of Technological Learning, Innovation and Development*, 2(4), 274-293
- Jacobides, M. G., T. Knudsen, et al. 2006. Benefiting from innovation: Value creation, value appropriation and the role of industry architectures." *Research Policy* 35(8): 1200-1221.
- Inkpen, A.C. and Moffett, M.H., 2011. *The Global Oil & Gas Industry: Management, Strategy & Finance*. PennWell Books.
- Klepper, S., 1996. Entry, Exit, Growth, and Innovation over the Product Life Cycle. *The American Economic Review*, 86(3), 562-583.
- Krafft, J. and F. Quatraro, 2011. The Dynamics of Technological Knowledge: From Linearity to Recombination. In Antonelli C. (Ed), *Handbook on the Economic Complexity of Technological Change*. Cheltenham, Edward Elgar.
- Krafft, J., F. Quatraro, and Saviotti P. P., 2014. Knowledge characteristics and the dynamics of technological alliances in pharmaceuticals: empirical evidence from Europe, US and Japan, *Journal of Evolutionary Economics*, 24, 587-622.
- Maleki, A., 2013. Can a mature resource-based industry become high-tech? Transformations of sectoral innovation systems in upstream petroleum industry. *Journal of Science & Technology Policy* 5(4), 83-105.
- Malerba, F., 2006. Innovation and the evolution of industries. *Journal of Evolutionary Economics*, 16(1), 3-23.
- Malerba, F., 2007. Schumpeterian patterns of innovation and technological regimes. In Hanusch H. and Pyka A. (Eds), *Elgar companion to neo-Schumpeterian economics*. Cheltenham, Edward Elgar.
- Malerba, F. and L. Orsenigo, 1996. Schumpeterian patterns of innovation are technology-specific. *Research Policy*, 25(3), 451-478.
- Malerba, F., (Ed) 2004. *Sectoral Systems of Innovation Concepts, Issues and Analyses of Six Major Sectors in Europe*. Cambridge, UK, Cambridge University Press.
- McGahan, A. M. and B. S. Silverman, 2001. How does innovative activity change as industries mature? *International Journal of Industrial Organization*, 19(7), 1141-1160.
- Mowery, D.C., 2015. Steven Klepper and business history. *Industrial and Corporate Change*, 24(4), 755–768.
- Nelson, R.R. and Winter SG, 1982. *An Evolutionary Theory of Economic Change*. Cambridge, MA, Harvard University Press.

- Pavitt, K., 1985. Patent statistics as indicators of innovative activities: Possibilities and problems. *Scientometrics*, 7(1), 77-99.
- Rajan, S., 2011. Future Technologies of the Oil Field. *Technical Leaders*, 7(3).
- Robertson, P., Smith, K. H., & von Tunzelmann, N., 2009. Innovation in low-and medium-technology industries. *Research Policy*, 38(3), 441-446.
- Saviotti, P. P., 2011. Knowledge, Complexity and Networks. In C. Antonelli (Ed) *Handbook on the Economic Complexity of Technological Change*. Cheltenham, Edward Elgar.
- Schumpeter, J.A., 1934. *The theory of economic development*. Cambridge, MA, Harvard Economic Studies.
- Schumpeter J.A., 1942. *Capitalism, Socialism and Democracy*. New York: Harper & Row
- Steinmueller, W. E., 2000. Will new information and communication technologies improve the 'codification' of knowledge? *Industrial and Corporate Change*, 9(2), 361-376.
- Teece, D. J. and H. O. Armour, 1976. Innovation and divestiture in the US Oil industry. In Teece D. J. (Ed), *Vertical Integration and Vertical Divestiture in the U.S. Oil Industry*. Stanford, Stanford University Institute for Energy Studies.
- U.S. EIA, 2011. *Performance Profiles of Major Energy Producers 2009*. Washington, DC, U.S. Energy Information Administration.
- Vale, M. R. and J. Caldeira, 2008. Fashion And The Governance Of Knowledge In A Traditional Industry: The Case Of The Footwear Sectoral Innovation System In The Northern Region Of Portugal. *Economics of Innovation & New Technology*, 17(1/2), 61-78.
- Von Tunzelmann, N. and V. Acha, 2005. Innovation in 'low-tech' industries. In Fagerberg J., Mowery D. C. and Nelson R. R. (Eds), *the Oxford Handbook of Innovation*. Oxford, Oxford University Press, 407-432.
- Wang, Q. and N. von Tunzelmann, 2000. Complexity and the functions of the firm: breadth and depth. *Research Policy* 29(7-8): 805-818.
- Weston, J. F., B. A. Johnson, et al., 1999. Mergers and restructuring in the world oil industry. *Journal of Energy Finance & Development*, 4(2), 149-183.
- Wintersteller, W., 1993. *The Role of Technology in the Upstream Petroleum Industry*, Mining University Leoben, Leoben Austria, dissesation.
- WRTG, 2008. Oil Price History and Analysis, <http://www.wtrg.com/prices.htm> accessed on 05/04/2016.



## APPENDIX 1: Measures of Knowledge Base Complexity

We employed Social Network Analysis (SNA) and its powerful toolbox to characterize the connectivity of the network as measure for complexity. A matrix of co-occurrence of technological classes is formed to represent the knowledge network where the value of each cell is the number of inventions for which two technological classes appeared jointed together (Krafft et al., 2011).

The *degree of centrality* of a node is used as one of the centrality measures, describing how strong is the level of connectivity of a node (Krafft, et al 2011). Formally, the following equation expresses the measure of *degree of centrality* ( $DC$ ):

$$DC_n = \sum_{i \in N, i \neq n} l_{ni} \quad (2)$$

Where  $n$  represents the nodes and  $l$  represent the links.

The *degree of centrality* is defined as the number of links of one node with other nodes of the network. Because this measure is affected by the network size, it is often divided by its maximum value to provide a normalized proxy (Krafft et al, 2011), as shown in the following equation:

$$NDC = DC_n / (N - 1) \quad (3)$$

In order to create a measure of connectivity at the level of a network, we rely on the *average* of the degree of centrality of all nodes in the network. Following (Krafft et al, 2011), we used the *average* measure of *degree of centrality*, weighted by relative frequency. This takes into account the highly unequal strength of the nodes, giving higher weights to important technological classes. Accordingly, the measure of complexity of the knowledge is the *weighted average degree of centrality* ( $WADC$ ) as follows:

$$WADC = \sum_n [NDC_n * (P_n / \sum_n P_n)] \quad (4)$$

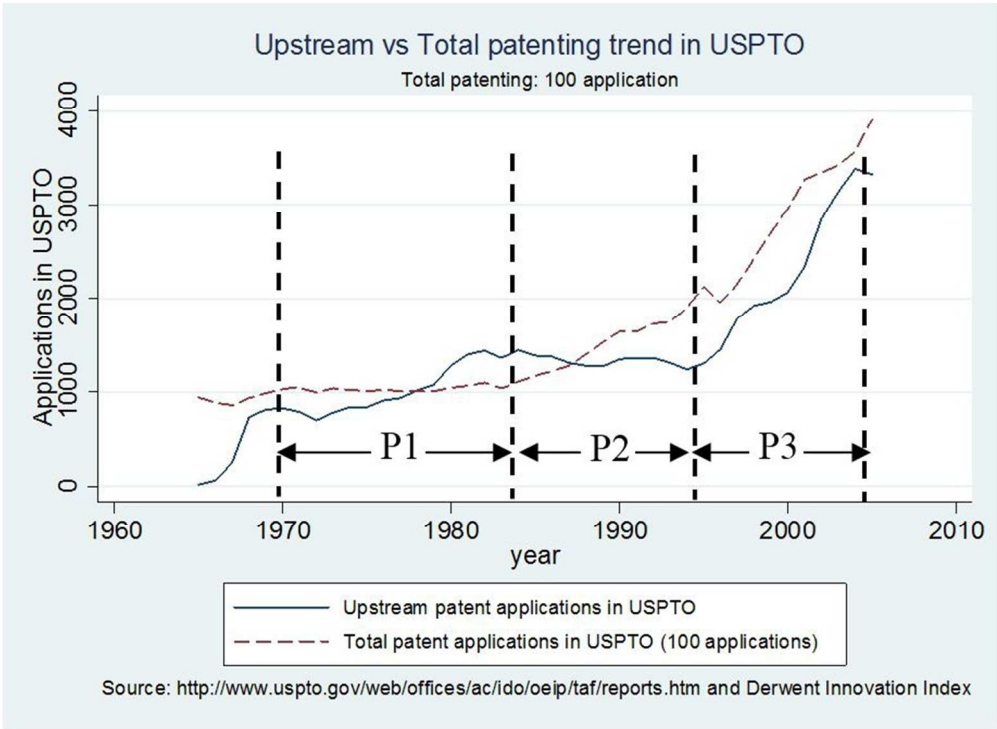
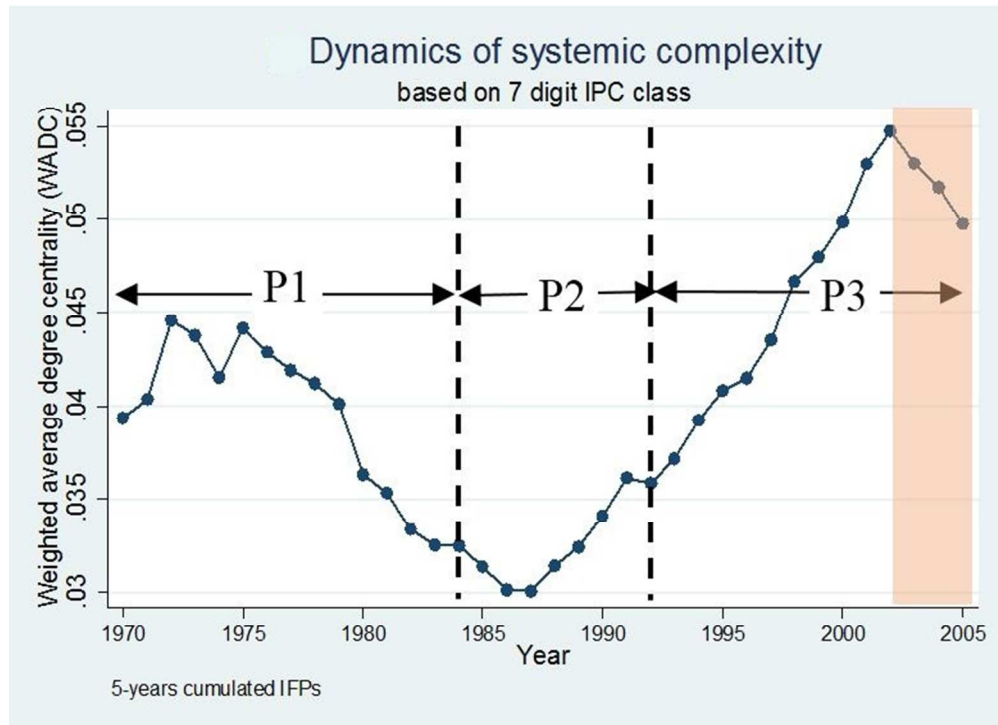


Figure 1  
Figure 1  
243x177mm (96 x 96 DPI)



Some data are missing in the post-2002 period (faded)

206x170mm (96 x 96 DPI)

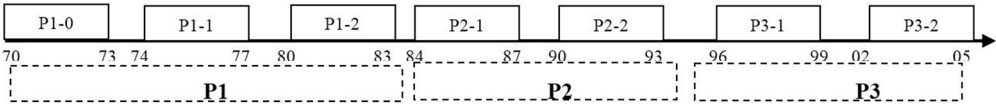


Figure 3  
Figure 3  
338x44mm (96 x 96 DPI)

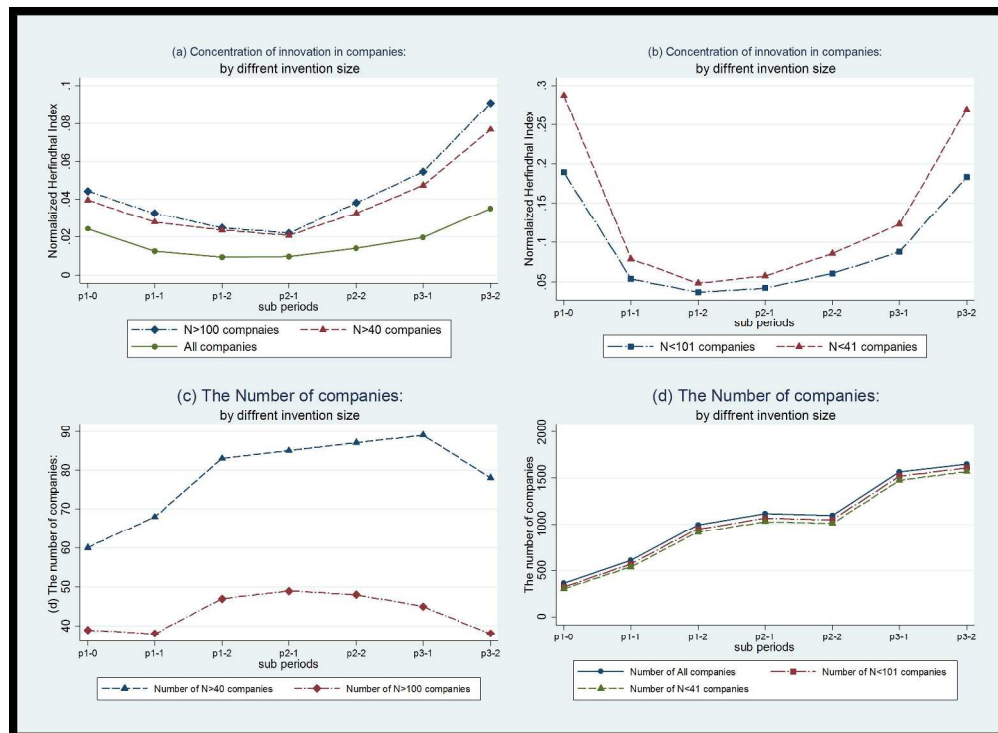


Figure 4

Figure 4

888x650mm (96 x 96 DPI)

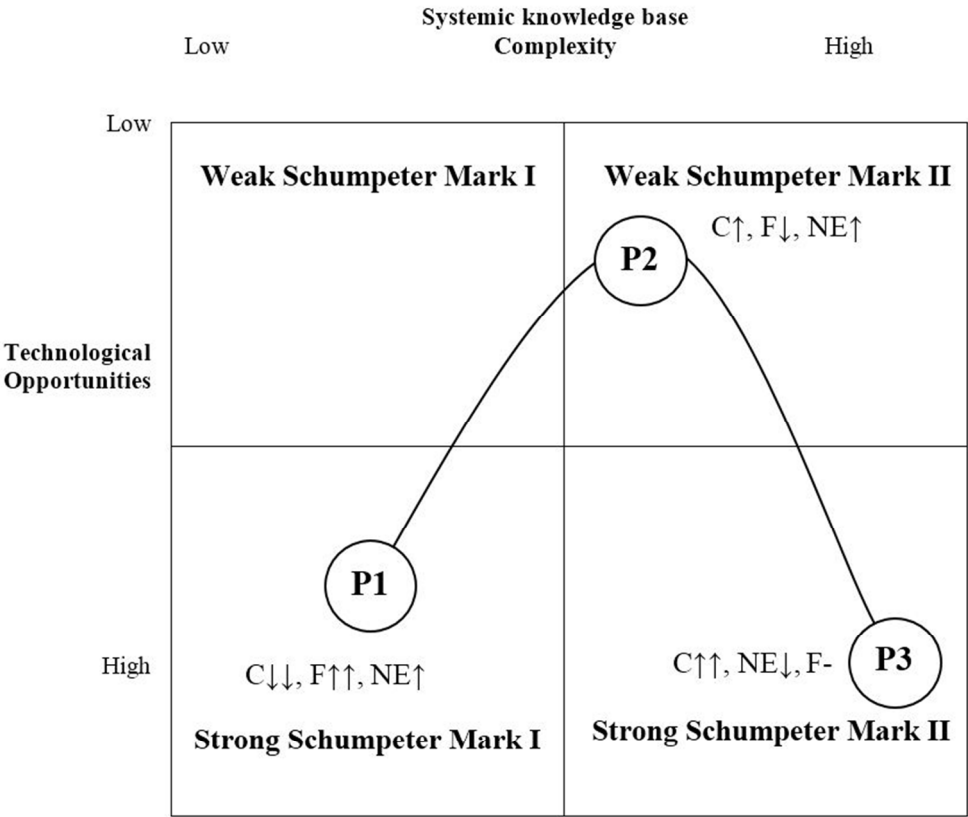


Figure 5  
Figure 5  
228x193mm (96 x 96 DPI)

<b>Schumpeterian patterns of innovation</b>	Schumpeter Mark I Widening	Schumpeter Mark II Deepening
Concentration (C)	↓	↑
Number of firms (F)	↑	↓ -
Entry of new firms (NE)	↑	↓
Stability of ranking (STR)	L	H

New firms' share of patents: by size

Sub periods	1 IPFs min size			5 IPFs min size			10 IPFs min size		
	IPFs Existing Innovators	IPFs New Innovators	Share of new entry (NEP)	IPFs Existing Innovators	IPFs New Innovators	Share of new entry (NEP5)	IPFs Existing Innovators	IPFs New Innovators	Share of new entry (NEP10)
p1-1	1297	693	34.82	1272	222	14.86	1222	108	8.12
p1-2	2205	1232	35.85	2166	442	16.95	2062	298	12.63
p2-1	2802	1033	26.94	2714	195	6.70	2588	67	2.52
p2-2	2528	1112	30.55	2459	223	8.31	2348	97	3.97
p3-1	4226	1957	31.65	4127	595	12.60	3952	337	7.86
p3-2	5291	1732	24.66	5089	203	3.84	4853	45	0.92



Periods	1 <sup>st</sup> period	2 <sup>nd</sup> period	3 <sup>rd</sup> period
<b>Schumpeterian pattern of innovation</b>	Strong I	Weak II	Strong II
Concentration (C)	↓↓	↑	↑↑
Number of firms (F)	↑↑	↓	-
Entry of new firms (NE)	↑	↑	↓